Chapter

Visualizing the Impact of COVID-19 in the Mobility Dynamics - A Dashboard Framework for Decision Support in Smart Cities

Nuno Alpalhão, Miguel de Castro Neto and Marcel Motta

Abstract

Being mobility one of the biggest challenge's cities face today, the COVID-19 pandemic reinforced this challenge and caused a deep structural change in the mobility of the multilayered dynamic framework of Smart Cities. The need to supply decision support systems to city authorities is higher than ever. Planning and managing mobility in Smart Cities has become more challenging, as the amount of information available and the pressure to enforce sustainable and secure policies increases, stakeholders require faster and more targeted actions. Dashboards are powerful tools that can be used in this context to provide, in an understandable manner, multidimensional information otherwise unavailable in classically static visualizations, as these tools offer a reliable foundation for decision support systems. This chapter goes through the required visualization techniques used to produce meaningful dashboards, to both showcase spatial and temporal trends in the context of mobility in Smart Cities following the COVID-19 pandemic. A general framework for analyzing mobility patterns is suggested by gathering methods and techniques recently developed in the literature.

Keywords: Smart Cities, mobility, COVID-19, decision support, dashboard, spatial and temporal trends

1. Introduction

The exponential growth and availability of data has opened the possibility of visualizing a city and all its layers in a previously unavailable smart way. We define the Smart Cities framework as an urban provider of several services clustered into different nonexclusive layers in a unified way [1], such clusters can be characterized as Mobility, Environment, Government, Economy, People and Living [2]. This digital transformation process cities face today is leading to a new reality where urban space is taking advantage of information and communication technologies and data science to answer present and future challenges, namely, to become more efficient in services and infrastructures management in order to deliver quality of life to the people who live, work or visit the city [3]. When developing a framework to support decisions in any of these layers one must always consider the amount of information available and its purpose. In this context it is natural to introduce a dashboard as a visualization tailored to give support to smart city agents, from managers to policy makers, in order to both understand and act on these complex matters [4] in a readily available manner and arranged on a single screen [5].

The global pandemic scenario caused by the Covid-19 pathogen raised many questions in terms of measuring and understanding its impact in multiple fronts (e.g. healthcare, economy, tourism). Addressing these questions became a critical task in tailoring and evaluating strategies to tackle the pandemic and minimize its effects, especially in the context of the Smart Cities. Naturally, a massive influx of dashboards started being developed, published and shared all over the internet by institutional agents, academia and industry. More often than not, these dashboards seem to lack well-defined guidelines in terms of their design choices and/or attempt to represent information in ways that are either unclear or dubious [6]. This diagnosis is one of the main drivers for writing this chapter and, hopefully, should provide an adequate reference guide for designing simple and insightful dashboards.

In this chapter we will provide a step-by-step dashboard design prototype applying structural guidelines [7] on how to deliver such an essential tool within the scope of mobility and the impact it suffered due to the Covid-19 pandemic in the city of Lisbon in Portugal. We will provide a broadening of the concepts required and encourage the reader to apply this methodology in any case within the framework of decision support in Smart Cities.

The proposed solution relies on a Javascript backend engine executed with Python programming language [8], in line with the state of the art. In comparison with other implementations, our dashboard improves the understanding of the impact of the Covid-19 pandemic by synthesizing visualization concepts and techniques gathered in the literature. This way, it is introduced a novel approach to better visualize mobility patterns in the context of Smart Cities.

2. State of the art

As defined in the literature, a dashboard is "a visual display of data used to monitor conditions and/or facilitate understanding". While there is not a clear definition in terms of its format, dashboards usually "combine different elements (e.g., charts, text, legends, filters, etc.) into a cohesive and coordinated whole that allows people to see and understand their data" [7].

In the field of mobility, it was identified a set of relevant dashboards that attempt to highlight trends and patterns by using clear visualizations and metrics, as shown in **Figures 1** and **2**:

Since the Covid-19 outbreak, Google started to release periodic reports [9] highlighting mobility changes at the city level, by using a category breakdown (e.g. Retail & recreation, Grocery & pharmacy, parks). While this report could arguably be described as a dashboard, it conveys information using data visualization tools and techniques to provide understanding over a certain event. In a simplistic manner, it defines a ratio metric to highlight the change in mobility caused by the policies and measures to tackle the Covid-19 outbreak. Additionally, it uses a line chart to analyze fluctuations over the previous weeks. Google also ensures the statistical significance of the information displayed by removing cities and categories which are not relevant or cannot be properly subject to analysis. On the other hand, the limited scope and lack of interactivity of this report could be pointed out as shortcomings and could be improved.

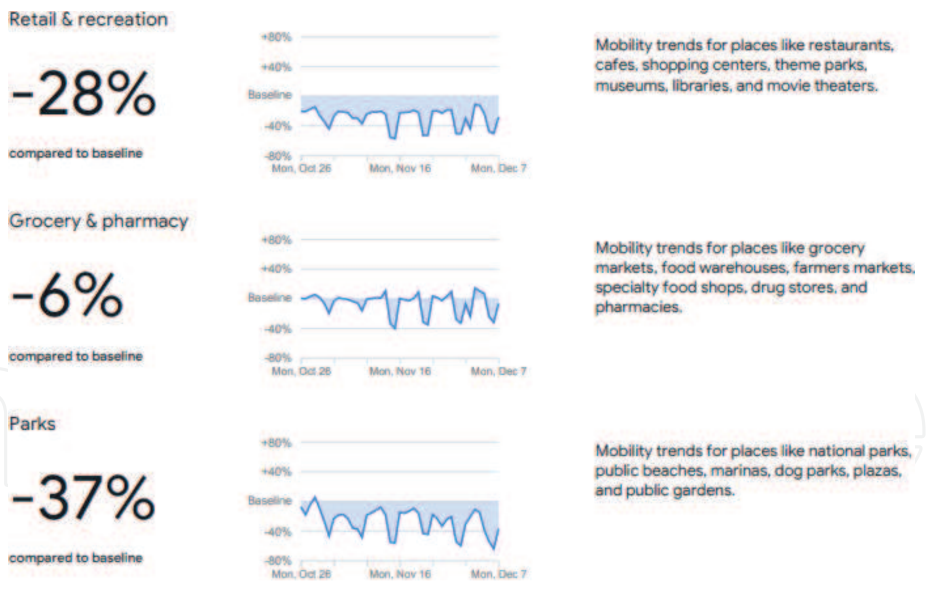

Figure 1.
Google's COVID-19 community mobility reports.

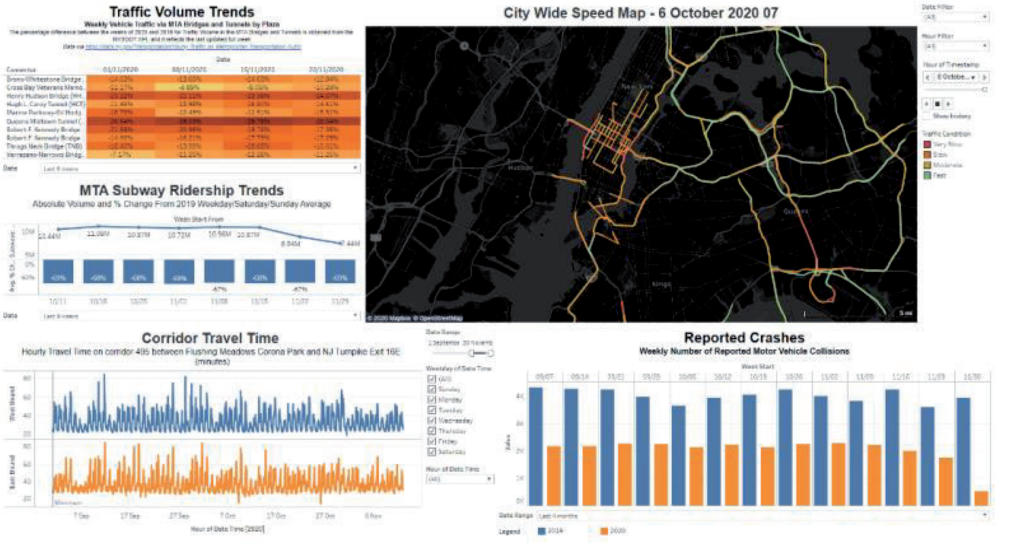

Figure 2.
C2SMART COVID-19 data dashboard.

In **Figure 2**, an interactive dashboard is proposed by C2SMART [10] to visualize daily traffic conditions and report changes in commuting patterns in the city of New York since the Covid-19 outbreak. This dashboard consists of combining several data sources (i.e. taxi, subway, traffic jams and collisions) and techniques to provide a complete picture of the impact of the pandemic on transportation systems as it unfolds. Given the nature of data, we are once again presented with elements that can better display the spatial–temporal distribution of mobility: (a) a map visual displays the traffic flow for the main roads in the city; (b) a heatmap visual shows the year-over-year (YoY%) difference ratio in traffic volume; (c) a line-bar chart showing absolute and YoY% subway ridership data; (d) a line chart showing hourly travel times for a selected road; and (e) a bar chart showing the weekly reported crashes between 2019 and 2020. The depth of this dashboard poses as a great example for the usage of data visualization for analyzing the effects of Covid-19 in mobility. Nonetheless, it might present some challenges in terms of complexity when using the several available filters and interpreting the information in an adequate manner.

3. Mobility in the urban context

Mobility in the Smart City context is defined as the essence of contemporary cities, in other words it defines the interactions of all moving parts in the urban context with multiple and distinct information sources ranging from traffic sensors to telecommunications data. A concept such as this one can be used in the definition and planning of multiple services in the urban area, such as a major factor in a smart and sustainable urban planning, an economic proxy for socio-economic characterization a feature in implementing and monitoring security in cities and so on [11].

As we have mentioned in the beginning of this chapter, mobility is only one of the multiple layers in the framework of Smart Cities, from which new insights can be reached with the simultaneous use of other sources of information either explaining or being explained by it. That is, understanding mobility alongside other determinant factors, in the context for Smart Cities, allows to answer a variety of questions about how cities and their inhabitants interact, at a certain point in time and space. Intuitively, the answer is always dependent on the intent of the visualization itself, but good practices are transversal to all problems [12].

For the dashboard built later in this chapter we will represent mobility by encoding traffic data in the form of geometric objects to map and describe commuting events happening throughout the city of Lisbon between 2019 and 2020, for the months of September and October. Additionally, we will also be using telecommunications data in the same spatial and temporal range in the form of Origin Destination (OD) matrices [13] to understand and quantify how many people move between census tracts of the city. Due to the sensitive nature of the communications information, all the data related to the OD matrices used to feed the visualizations was artificially generated from the original source. As we will see in the sections bellow, the usage of these two data sources will allow us to visualize mobility patterns across the day before and after Covid-19.

4. Covid-19 impact scenario

As it is known the Covid-19 has been a prevalent pandemic that significantly changed the way people conduct their lives [14, 15], especially when it comes to mobility, as lock down and isolation measures restricted commuting and traveling to an unprecedented extent. With such a significant transformation it is natural that the need for governments to reinforce well-informed policies is higher than ever, with the ambition of moving to data-driven public policy making, especially in the urban areas where the incidence is more pronounced. From our definition of mobility, it comes naturally that a study on the impact of this pandemic is not only desirable but a necessity in the context of Smart Cities, particularly now that we begin to have sufficient historical data for the period of this pandemic. However, presenting and exploring data to effectively turn it into valuable information requires some considerations, such as: the definition of the observed event, the toolset and structure used in the report, the scope of the report, the target audience, and its main objectives.

Below we will start to define all the structural requirements along with a set of good practices for a successful and impactful dashboard.

4.1 Problem definition

In order to adjust city wide services and policies, such as public transport, security, traffic management and infrastructure development, city planners require not only the latest information regarding the current state of mobility but also how historically it changed in regard to the impact of the Covid-19 pandemic or, in other words, what is the new "normal" mobility patterns in the city of Lisbon?

We are expected to define and visualize the current context of the city's mobility as well as to be able to differentiate the impacts caused by the Covid-19 pandemic.

4.2 Visualization requirements

First and foremost, it is essential to outline a storytelling narrative behind your visualization to provide the proper context to the data, to highlight its relevant characteristics and, ultimately, to deliver insights.

Creating a visualization that can express the state of mobility at a given point in time, is the main objective, but having the city as a single entity is not enough to fully understand the dynamics of smaller partitions, such as neighborhoods and main roads. We identify three main requirements for a desirable dashboard: (a) a zoom in and out approach needs to be available to the user; (b) a clear temporal trend comparison is a must to understand the impact and the ways to administer the changes caused in the population's mobility; and (c) measures to understand if the current state of mobility is expected and if not, where it is deviating from the norm.

4.3 Scope

Will it be possible to use this dashboard for a different purpose, for example: can it be used to aid police officers in choosing patrol routes? By adding information would we lose on the main problem? These are the questions you should be making even before you start thinking visually, since they will surely affect the outcome and longevity of the dashboard itself.

4.4 Target audience

To whom the dashboard is aimed for should deeply impact its design, as you should not expect the end user to have the same degree of expertise in a subject as you do.

Given the importance of Smart Cities for policy makers and institutional agents, the main target of the proposed dashboard should be stakeholders whose responsibility is to tailor and gauge the conditions of the city's infrastructures, services and facilities made available to its inhabitants, to improve the management of resources, namely public transport, and to promote well-being. But taking into consideration the possible scope option mentioned in the section above, what if the dashboard was intended to police officers as well? Given that their line of work requires specific and fine-grained information to recognize which specific streets might need more attention, new layers of information would be needed to provide such an understanding.

5. A dashboard

5.1 Prerequisites

Before we can begin, we need to fully understand how we want to represent our problem set and the sources available for this purpose. For a descriptive visualization to successfully work it is required to operate under some well-founded assumptions.

For the problem at hand, we have available traffic jams, telecommunications OD matrices and geolocated layers such as metro stations, bus stops and road infrastructure. But how can we use them to represent such a broad term such as mobility? It is in this part of the chapter that we will start warning the reader that a single correct answer does not exist, different interpretations of the definition of the problem will naturally lead to different solutions, nevertheless, a substantiated approach that is able to effectively solve the problem is always of great value.

It is known that traffic jams are mainly caused by two intrinsically distinct factors [16]: (a) Daily commuting, a problem caused by a recurrent overload of the road system (mostly during week days) in both the home to work commuting (typically during the morning) and again in the analogous work to home commuting (typically during the afternoon), a problem most cities still struggle to solve; (b) A random event, road accidents or city wide events such as a sports match, can cause sporadic traffic jams. While the second point can bring some great insights on how to manage mobility given an external factor or event, it is the first point the allows us to consistently take a snapshot of the daily dynamics of mobility in a city, in order to characterize such a diverse structure as a city, recurrent events are always desirable.

With such a mindset we can consistently describe a factor of the city's mobility ecosystem on a daily or even weekly basis. To broaden our understanding of the mobility dynamics, using the OD matrices data, given a traffic jam, we can identify from which census tracts of the city people came from and went to.

Given the real time state of traffic, one cannot accurately identify the cause of a traffic jam, but if, for the same location, there is an occurrence of traffic jam in the morning and in the afternoon, and as it is known, commuting is recurrent, so with a daily, weekly, or even monthly overlay, we can start to visualize the typology of these jams and their implications.

5.2 Current state of mobility

The term current can be misleading, as the current state of mobility in the city is not solely described by the real-time state of traffic jams but by its past state as well. In the assumptions made, the recurrence of daily traffic jams can be identified as an overload or bottleneck on the road system caused by the commuting of people, nevertheless, to give the ability to the user to characterize and visualize a traffic jam, as commuting related or not, an encoding of the whole day needs to be present as well.

As one can see in **Figure 3**, the user has access to the daily state and degree, with a clean color encoding, green for home to work commutes and red for work to home, of traffic jams in the city and is simultaneously able to understand the extent of recurrence of these events. For a given temporal window (in the image set as "Daily"), an algorithm identifies and defines immediately, with a given degree of confidence, each commute as the reoccurrence of a traffic jam in the morning and afternoon in the same location, by analyzing the consistency of origin and destination census tracts between the morning and afternoon throughout the day or week, implicitly it already characterizes the mobility dynamics of a city by defining commuting of people as a daily occurrence through the same location, causing traffic jams. This visualization allows the user, in a very clear and succinct way, to spatially understand how mobility is being conducted, and the degree of severity of the overload in the road system. Allowing zoom in and out operations to clearly see the direction in which mobility is and historically where it has been going. Additionally, by choosing a concrete period and temporal aggregation on the top menu, the user can click the submit button to change the map, treemap and bar chart visualizations as desired.

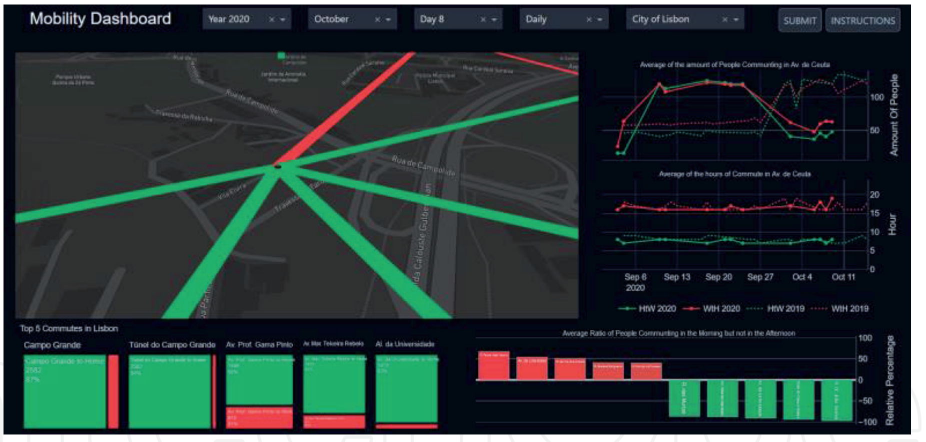

Figure 3.
Dashboard prototype [17].

By itself, the map is not enough to give an understanding of numerically how many people commute. How do we compare different commutes that are spatially separated? In the following visualizations we will focus on each commute as a bi-daily occurrence of a traffic jam on the same location and its origin and destination census tracts, as identified by our algorithm.

To understand the dimension and difference between different commutes, using the OD matrices we can calculate the total number of people that commuted from their homes to their work (HtW) and from work to their homes (WtH) for each traffic jam, under the assumption that it is caused by commuting. Naturally to guarantee, with a given degree of confidence, an average of the moving window for each type of commuted related jam can be made.

Having this information for the current state of mobility for that temporal window, a visualization can be created to compare different commutes and allow the user to understand the numeric difference of each unique commute and have a clear notion of the current state by comparing them.

It seemed appropriate to choose a treemap visualization [18] as shown in **Figure 4**, to allow the user not only to understand the number of people commuting but also to visualize the relative difference between them. In order to prevent an overcrowding in the visualization we chose to show only the top five commutes in terms of absolute number of commuters. Intuitively for this problem other types of visualizations could also have achieved the same level of effectiveness as a treemap visualization. For example, a pie chart could relay a better comparison within unique commutes but would not be so successful in displaying the comparison between distinct commutes. Although different choices could be made here, one should always prioritize on how the user should comprehend the data.

Now that a comparison of the number of commuting people between home and work has been made, given its spatial distribution, there is still the need to better understand how the difference in the number of people between the home and

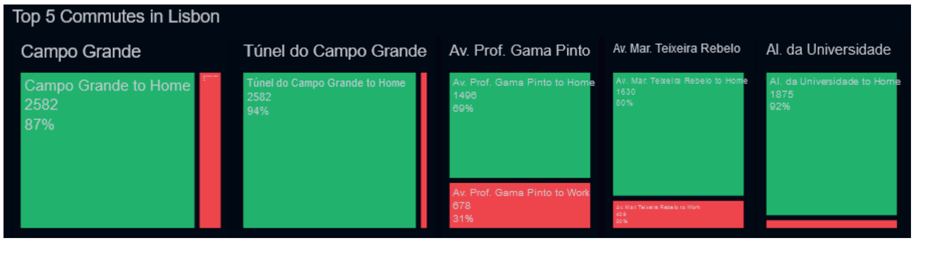

Figure 4.
Treemap visualization.

work commutes affect mobility. Intuitively, most people might commute to work daily in the same hour, participating in the same jam, but one cannot expect all of them to behave similarly, sharing again the same schedule when going back home. This translates in a consistent numeric difference that can be used to both characterize and differentiate different commutes.

Above in **Figure 5**, we have created a bar chart to visualize and compare such difference, each bar represents the relative difference of the number of people that commuted from home to work (HtW) by the number of people that commuted from work to home (WtH) for each commute, centered on the zero axis. In other words, the percentage delta of people that participated in a traffic jam in the morning for their morning commute and also participated in a traffic jam, in the same location in the afternoon. Again, to prevent overcrowding of the chart, only the top five highest and lowest ratios were shown. This visualization allows the user to understand how the main commutes in the city are differentiated spatially but also temporally from the morning to the afternoon, providing a new dimension in the comprehension of the city's dynamics.

5.3 Spatial–temporal data

The previous visualizations provide an understanding of the current state of mobility in a city given a temporal window by visualizing where and how

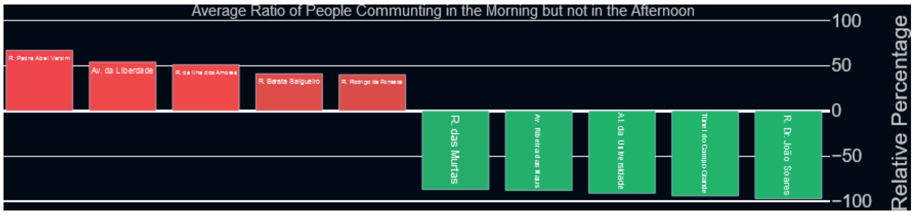

Figure 5.
Bar chart visualization.

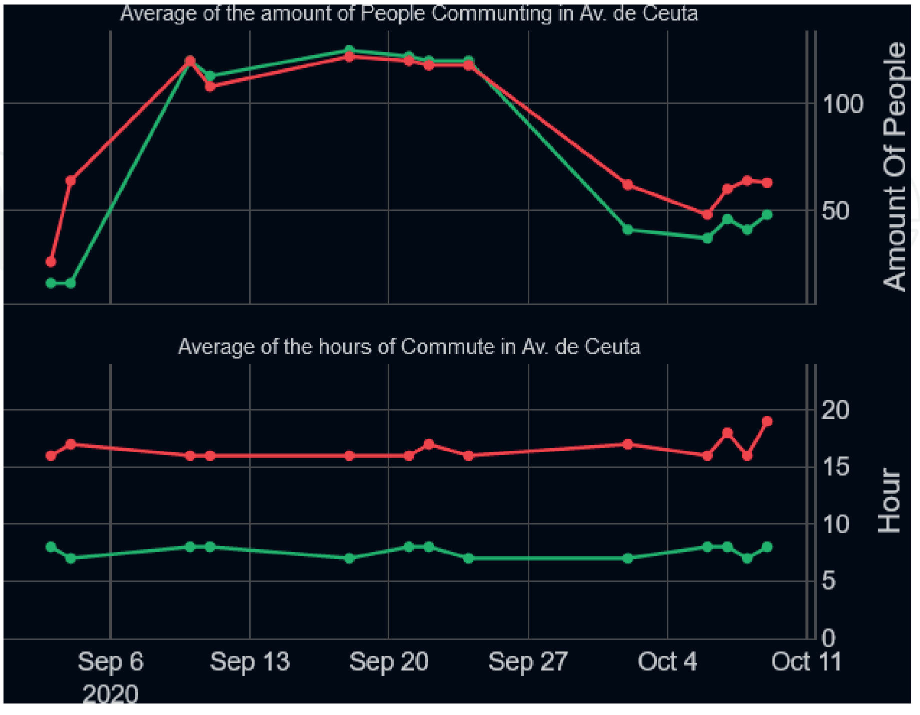

Figure 6.
Line chart visualization.

commutes are made. Nevertheless, to fully convey the natural change of how people commute throughout each yearly cycle, we need to analyze each individual jam location.

As we can see in **Figure 6**, by clicking in any specific point of the map, the user can access the full historical values of the amount of people that commuted in that location through the whole year and also, the average weekly hours in which the commute related jam occurred, this allows the user to grasp the existing seasonal trends to better discern the fundamental differences between the morning and afternoon commutes. By following the color encoding used in the map, using the greens for home to work transitions and reds for work to home, we create a cohesion in the dashboard that provides an ease of recognition for the user.

5.4 Measuring Covid-19 impact

To study the impact of such a prolonged event we first need to frame it temporally, as it is known the Covid-19 pandemic started spreading worldwide approximately in the month of February of 2020 and to the day it is still active. Naturally, a comparison to a period where the pandemic was not active is required, nevertheless due to seasonal trends the comparison needs to come from homologous months from different years.

As we can see in **Figure 7**, by using dotted lines, we can add the previous year's "Covid-19 free" information in the same line chart, where we can perfectly distinguish and compare the possible impact in mobility in terms of absolute values and hourly occurrence. The intention in the use of dotted lines in this visualization is to covey the attention of the user immediately, but also to set the previous year as a sort of target or something to be perceived as a goal, reflecting a hope in trying to achieve a "normal" mobility again.

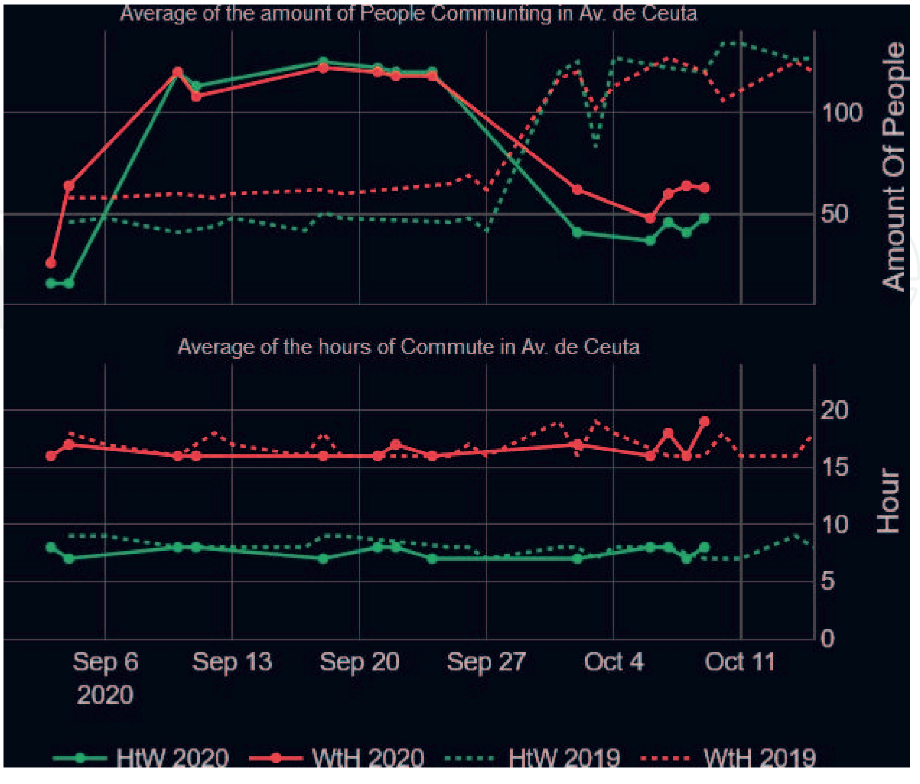

Figure 7.
Visualization to offer a year-by-year comparison.

6. Conclusion

In light of the Covid-19 outbreak and to support a data-driven urban management strategy, the need for data analytics tools is in the forefront of policymaking. In practice, this approach proves to be an interesting path for presenting and exploring shifts in mobility patterns, while being robust enough for answering transversal questions regarding the cities and its dynamics with the ambition of supporting data-driven policy making in pandemic situations.

This chapter presented and discussed dashboard solutions designed to analyze the impact of Covid-19 in mobility and proposed a framework for data visualization in the context of the Smart Cities using dashboard techniques and following a set of clear goals and good practices to reach them. Moreover, a dashboard prototype was proposed for visualizing changes and shifts in the local dynamics given historical data obtained before and after the pandemic outbreak in 2020.

Our findings seem to fit the current literature, as one can see, in **Figure 4** the use of a treemap visualization can be highly scalable while providing an efficient use of space in the dashboard itself [18], defining the problem, scope and target audience is essential prior to the development of any visualization [7, 12] and understanding Smart Cities as multilayered entities is indispensable in order to provide any kind of meaningful insights [1, 3], especially when dealing with mobility [11, 16].

Furthermore, the visual components proposed attempt to look at mobility data from multiple perspectives, in line with previous works; for instance, time can be visualized as a continuous dimension in a line chart to represent a historical series, or it could also be visualized as an ordinal variable in a bar chart to represent distributions across days of the week [7]. The proposed components should also allow to compare different points in time and space [7], in order to identify seasonal trends and/or spatial concentration, which could be achieved by line charts, maps and treemaps. The ideas herein discussed and the proposed guidelines are a small contribution to consolidate the application of dashboards in the field of the Smart Cities and, hopefully, this chapter could be used as inspiration for authors and contributors for further development in this field of study.

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